Applied Energy 371 (2024) 123502

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A new bottom-up method for classifying a building portfolio by building type, self-sufficiency rate, and access to local grid infrastructure for storage demand analysis

Steffen Schedler [a,*], Stefanie Meilinger [a,c], Tanja Clees [a,b]

[a] Hochschule Bonn-Rhein-Sieg, University of Applied Sciences, Department of Engineering and Communication, Institute for Technology, Resource and Energy-efficient Engineering (TREE), Grantham-Allee 20, 53757, Sankt Augustin, Germany

[b] Fraunhofer Institute for Algorithms and Scientific Computing SCAI, Schloss Birlinghoven, 53757, Sankt Augustin, Germany

[c] Hochschule Bonn-Rhein-Sieg, University of Applied Sciences, International Centre for Sustainable Development (IZNE), Grantham-Allee 20, 53757, Sankt Augustin, Germany

ARTICLE INFO

Keywords:
Classification of buildings
Open data
Energy demand
Metal hydride storage
Potential analysis

ABSTRACT

A building's energy storage demand depends on a variety of factors related to the specific local conditions such as building type, self-sufficiency-rate, and grid connection. Here, a newly developed bottom-up procedure is presented for classifying buildings in an urban building portfolio according to specific criteria. The algorithm uses publicly available building data such as building use, ground floor area, roof ridge height, solar roof potential, and population statistics. In addition, it considers the local gas grid (GG) as well as the district heating (DH) network. The building classification is developed for identifying typical building situations that can be used to estimate the demand for residential energy storage capacity. The developed algorithm is used to identify potential implementation of private photovoltaic(PV)-metal-hydride-storage (MHS) systems, for three scenarios, into the urban infrastructure for the city of Cologne. As result the statistical confidence interval of all analyzed buildings regarding their classification as well as corresponding maps is shown. Since similar data sets as used are available for many German or European metropolitan areas, the method developed with the assumptions presented in this work, can be used for classification of other urban and semi-urban areas including the assessment of their grid infrastructure.

1. Introduction

As part of Germany's energy transition, the government aims to achieve a carbon-free national energy infrastructure by 2045. According to data from the Federal Ministry for Economic Affairs and Climate Action (BMWK) in 2022 [1], the residential sector represented 29% of end energy consumption in 2020. Of that consumption, approximately 70%–75% is attributed to the direct use of fossil fuels, primarily for heating and hot water. To reduce the overall energy demand in the residential sector, solar home systems are subsidized by the government, leading to an increase in local production of residential PV energy [2]. PV energy generation depends on geographic location, weather conditions, and the time of day, while residential consumption is based on residents' lifestyles and ambient temperature. As both, PV energy production and residential energy consumption are not sufficiently in tune with each other, the need for energy storage to improve local self-consumption increases.

Quantification and allocation of energy gain and use in urban, suburban, and rural areas are of most importance for planning and developing a future energy landscape. Especially grid developers need detailed energy curves in high spatial and timely accuracy to feed energy flow simulation and optimization tools such as MEgy [3,4] or MYNTS [5] to calculate an expansion of grid sections as infrastructure costs are high for installing permanent underground tubes or cables. When examining the private sector as an energy consumer, it is essential to evaluate also the accessibility of both gas grid and district heating. This is particularly crucial in urban areas where there is high population density and building concentration, with a high likelihood of buildings connected to these grids. This data can then be used in simulation studies e.g. to analyze the effects of decentralized feed-in into DH networks [6].

Usually classification methods of residential energy consumption are divided into a knowledge-based "top-down" or a data-driven "bot-

* Corresponding author.
E-mail addresses: steffen.schedler@h-brs.de (S. Schedler), Stefanie.Meilinger@h-brs.de (S. Meilinger), tanja.clees@h-brs.de (T. Clees).

https://doi.org/10.1016/j.apenergy.2024.123502
Received 7 December 2023; Received in revised form 19 April 2024; Accepted 17 May 2024
Available online 15 June 2024

tom-up" method of an excerpt area. These methods can be subdivided into either economical or technological methods for the top-down branch or statistical or engineering methods for the bottom-up branch [7]. While the statistical method uses buildings energy demand samples in regression with various possible parameter, the engineering method is based on the buildings characteristics to estimate an energy demand. The use of Geographical Information System (GIS) data to analyze energy topics in a bottom-up method is established and commonly used e.g., creating benchmark data for electric power system [8], looking at defossilization strategies of heating [9], to estimate an application potential of heat pumps [10] or to give a detailed distribution of heat demand [11]. [12] already incorporates several GIS data sources to create a multi criterion decision map. The local distribution of buildings in the area of interest has an important influence on the energy production, as also concluded by [13]. For all these reasons, the bottom-up approach with a strong influence of the engineering method was chosen.

In the residential sector, it is typical to use a building as the base unit for projecting energy. The possible solar roof generation, based on PV, depends on the available roof area of the building as well as on the solar resource and its spatial and temporal distribution. [14] reviewed the impact of PV on buildings onto their energy self-consumption. Data on solar resources are globally (e.g. SOLAR GIS [15]), or in higher resolution, locally (e.g. COSMO-REA [16]) available. From this data, PV power and PV yields can be calculated using state-of-the-art models (e.g. PVGIS [17]). In addition, pre-validated data on solar potential is already published by several environmental state agencies, e.g. by the State Agency for Nature, Environment and Consumer Protection (LANUV) of North Rhine-Westphalia (NRW) [18]. The latter has been used in this study to estimate solar PV potential.

Surplus renewable electricity from PV modules can be converted into hydrogen via electrolysis of water. This so called green hydrogen will play a significant role in the energy transition [19]. Hydrogen can be fed into the GG, which offers an additional infrastructure to store and deliver energy on a seasonal scale. This can be used to provide energy to households, which are connected to the GG. If already available, the GG will be first choice to store hydrogen, as no additional infrastructure is needed. Without a connecting GG, compact and safe MHS systems will be an option to store hydrogen long-term. This is because some metals and alloys have the ability to absorb hydrogen atoms and embed them in the metal lattice — together they form a stable metal-hydride. In this state, a good amount of hydrogen can be stored in a relatively small volume under moderate pressure and low temperatures [20]. The energy chemically stored in hydrogen can be reconverted to electricity by using a fuel cell. The whole hydrogen storage path counts therefore as power-to-power system. [21] for example, assessed various power-to-x strategies focusing on small-scale systems and their strengths and weaknesses.

Only few residential hydrogen storage systems have been realized yet, but their potential to safely store energy across seasons with very low energy loss is promising [22]. If needed, the hydrogen can be used for electricity as well as for heat production, depending on the local demand, which again depends on the building type as well as on the access to heat or GG infrastructure. For the future evaluation of possible implementation of hydrogen gas storage, the connection to existing infrastructure is an important selection criterion and therefore needs to be included in the analysis. The new method developed and described in this paper includes the power grid (PG), DH networks and the GG.

The building's energy balance depends on the electric and thermal load of the building. Each building has unique energy requirements determined by the number of occupants, their habits, and the building's materials and shape. To simplify the accumulation of diverse energy data the buildings are clustered around representative sample units. This typification is usually done via computational algorithms of GIS data on basis of a buildings characteristics e.g. its food print [23] or by its geometric ratio [24]. Several sources and tools for analyzing building data are available. [25] compared his method for several sources, while [26] made a comparison of 8 urban building energy modeling (UBEM) tools since 2009. The use of building data, such as a building's floor area and height, is very common and is used in all tools to estimate a building's energy demand. Less common is the inclusion of statistical data, such as population, to refine the energy data results. Only one of the tools mentioned in [26] is labeled with this capability, currently available for residential buildings. These tools aim to look at the demand side of buildings. The supporting infrastructure networks play a minor role in the analysis made with these tools. Although the latest tools include some support for network analysis, existing DH networks and GG are not included in the building classification. Heat demand of buildings can be spatially accumulated to balance municipalities and regions, as did [27] for a geographical analysis of energetic biomass use.

Bottom-up classification of buildings are usually performed for defined and limited areas. A comprehensive guide for region specification was implemented by the European Government. It defines areas in different sizes and density. The so-called Nomenclature of Territorial Units for Statistics (NUTS) are a common unit to differentiate and compare to other regions of the same definition [28]. The region chosen for this work belongs to the NUTS 2 region cluster. The regional focus is limited to residential areas in and around Cologne, fourth biggest city in Germany by inhabitants. As each city has its unique building portfolio, a detailed analysis of building types combined with their possible occupancy will result in a high spatial energy demand map suitable for planning future energy infrastructure. Especially access to gas- or heat grids might play an important role for optimization of energy storage demand and system sizing. Information about existing grid infrastructure are and need to be included in planning tools e.g. like [29].

To classify buildings according to their net energy demand, a bottom-up analysis of the regional building stock is carried out. The analysis is based on geographical and statistical open datasets for building size, roof solar potential and population. In addition to traditional distribution analysis of typical representatives of each building type, the analysis includes the energy production of PV systems and the energy demand at the individual building level. To further combine the analyzed building portfolio with an existing scenario set, the buildings' connections to different types of energy grids are considered. Next to an generally available electricity grid connection, buildings in urban areas are commonly connected to a gas grid or a local heating network. In this newly developed method the building type, electrical energy self-sufficiency, and grid-connection serve as criteria for building classification in a regional context. The classified building stock can be separated in clusters. In combination with distinguishing features of three relevant scenarios the data can provide insight on possible use of grid-integrated residential PV-MHS systems. Specific datasets for each scenario will serve as input parameters for a newly developed energy system model, based on energy flow simulation, that investigate the interaction of hydrogen production (from excess solar energy by electrolysis), storage in a metal-hydride tank, and hydrogen utilization in a connected fuel cell forming a local PVPtGtP (PV power-to-gas-to-power) network. The simulation model is presented in [4].

The developed method is presented in Section 2, introduced by preceding work specifying a framework: defining the building typology, selecting scenarios for possible implementation of the PV-MHS system, and obtaining and verifying data for suitability. After a targeted pre-processing of the different data sources, these sources have been integrated to a single database using various corrective processing steps of the building data and including continuous plausibility checks of the algorithm during development. Subsequently, all buildings are classified according to a predefined typology. Additional characteristics such as self-sufficiency and availability to existing energy networks are included in the targeted classification of buildings.

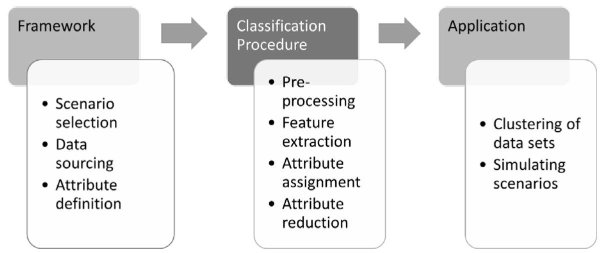

Fig. 1. Schematic diagram of the method developed.

First results showing the effectiveness of the building classification are presented in Section 3. In the following Section 4 these results are discussed w.r.t. their target use. A preview of future work, depending on the created classification data, finalizes the paper.

2. Methods, data sets, and region selected

The newly developed method presented in this paper is schematically depicted in Fig. 1. According to the context and the task in coherence with the selected scenarios, available input data sets are acquired from various publicly available data sources. Together with predefined building attributes, the data sets are passed to an algorithm to processes and modify the data sets in four steps.

1. Pre-processing to extract and harmonize data sets
2. Extracting building features and calculating interim attributes
3. Assigning of interim attributes and aggregation to target attributes
4. Reducing of data set to relevant data set to discard outliers

This classification procedure results in a clustered data set, which can be used to extract relevant parameter settings for scenario simulations. In the following this method is applied to the case of integrating residential PV-MHS systems into the Cologne building sector, considering the existing grid infrastructure for gas and heat. The framework is discussed in Section 2.1 defining the selected scenarios with an attached definition of target attributes in Section 2.2. In Section 2.3 the selected data sets are described, followed by the data processing of the classification procedure in Section 2.4.

2.1. Scenario selection

In the case of grid-integrated residential PV-MHS systems, the classification procedure is based on a set of target attributes describing the building types specific to the target scenarios. Three scenarios have been selected along the available energy grid infrastructure, in this case connections to electricity, gas, and heat networks. It is assumed that an urban building is connected only to the electricity grid or to the electricity grid and the GG or a DH network. In Germany, nearly 100% of buildings are connected to the electricity grid. However, due to the cost of installation, DH networks are limited in their expansion and tend to be concentrated in urban centers. GG networks are more extensive. In the case of Cologne they reach nearly into every suburb. Buildings connected to the different grids will have different energy system configurations. In a future hydrogen supported energy system the use of hydrogen gas and storage opportunities in an MHS are unclear, especially if taking into consideration the use of excess heat from the hydrogen conversation processes. Buildings connected to DH can benefit from a centralized MHS using the DH to transport excess heat to the buildings. Buildings connected to the GG can use the grid itself as hydrogen storage, but the generation of hydrogen presumably will be centralized. Use of hydrogen would occur in the individual buildings, allowing a heat recovery on cold days and therefore supporting the heating system, as well as lowering the power needs of the electricity grid or even feed-in of power. Buildings only connected to the electricity grid must implement the whole hydrogen storage path and handle their seasonal energy storage to gain benefit by raising their self-consumption. As a connection to the electricity grid is given in all scenarios, the scenarios are named ‘Power grid’ (neither DH nor GG connection), ‘District Heating’, and ‘H2 Gas Grid’. The distinctive description of the scenarios is listed in Table 1. Visualizations of these scenarios can be found in Fig. 2. The exemplary region studied in the following, namely the Cologne city area, houses about 1 million inhabitants in an area of about 405 km^2. The city’s utility service offers a gas grid (GG) reaching into nearly every district and four separated DH networks. In the area, about 143,784 buildings are listed as residential buildings according to [30] in 2020. These buildings differ in features of various characteristics and form an inhomogeneous building portfolio.

For assessing the energy demand of city areas, a bottom-up energy mapping method is used. To estimate the energy need of the building and their inhabitants various attributes about a building are collected or estimated. This method accounts for the grid connection, the building’s age, the number of flats and their floor space of a building as well as its number of inhabitants. As these data are not available for public use for each building in detail, an algorithm using open data sources from the government and municipal statistics is developed combining and assigning possible buildings parameters to each unit. These parameter sets are then consolidated into three main attributes as defined in the following Section 2.2. Clustering of buildings with similar parameter sets is possible through the use of these attributes. Districts with similar parameters form a nucleus by considering their spatial situation and result in sample districts and buildings for the scenario calculations.

2.2. Attribute definition

In order to classify the common building types within the limited region, three attributes were chosen.

1. building type
2. self-sufficiency rate
3. grid access

These attributes were extracted from the cluster of drivers associated with the scenario descriptions by trying to combine availability or derivation from known data sets with significance in the considered scenario of the sector analysis.

The **building type** is defined according to the Institute for Housing and Environment (IWU), which fulfilled the German part of a European-wide project EPISCOPE, classifying existing residential buildings according to age, size, number of flats, and further parameters [31]. All buildings are categorized based on their living area, the number of dwelling units in the building, and the location of the building in relation to other buildings (freestanding, semi-attached, or attached). In accordance with common typification, buildings are represented in four groups:

1. Single or double family house (SFH/DFH/SDFH)
2. Apartment building (AB) with 3–6 dwellings
3. Big apartment building (BAB) with 7–13 dwellings
4. Living quarter (LQ) including high-rise buildings with more than 13 dwellings

In seeking a representative net energy load for each building, the focus is on the two main drivers of energy use. According to the data analysis of BMWK in the years 2011–2019, the residential sector uses around 70% of its end energy demand for heating and around 30% for electricity (lighting, appliances, hot water, etc.) [1]. Overall, a building’s energy needs can be listed in three categories: electricity, heating, hot water. Each of these is caused by a mixture of dependencies from:

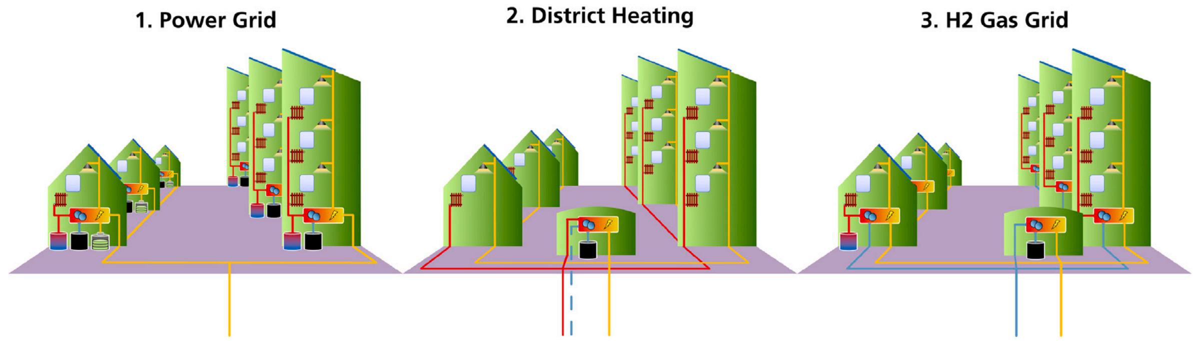

Fig. 2. Descriptive depiction of the scenarios: 1. Power Grid, 2. District heating, and 3. H2 Gas Grid — with the interconnecting grid between the buildings of electricity (yellow), district heating (red), and H2 gas (blue). Possible implementation of storages (MHS in black, thermal storage in red/blue, and battery (gray/green).

Table 1
Target scenarios for city district/living quarter evaluation.

Attributes\Scenario	Power grid	District heating	H2 Gas Grid
Grid Connection	Power grid only	PG, DH, potentially GG for DH-subnet	PG and GG
Presumably dominant building type	SFH and DFH	District-wise similar, leaning to greater share of MFH	District-wise similar
Self-sufficiency rate	Decent	Medium to low	Very low
MHS size and placement	Individual small units in each building	Big units in district subnet	GG used as seasonal storage, use of MHS only supportive
H2 conversion placement	Individual in each building	Central unit for subnet	Split generation and use
Alternative developments	Competition or combination with heat-pump	CHP or solar-thermal supported DH	Change of supply type
Operation	Electricity-driven	Heat-driven	Mixed
Grid simulation complexity	Simple, high similarity	Medium, single district unit	Complex, variant demand
Individual simulation complexity	Complex, various components	Medium, single district unit	Medium, variant demand

- building shape, materials, common walls, location, energy gain, ...
- number of flats in building
- flat size, infrastructure, ...
- number of inhabitants per flat
- inhabitant's habits, appliances, ...

To balance all these parameters and their variations is impossible. Therefore, the greatest impact on energy dependence is usually assumed to be determinant. Heating needs are calculated by square meter of the flat's ground surface, ambient temperature, and state of the building's insulation capacities. Electricity and hot water needs are mainly driven by consumption per inhabitant group. All electrical energy loads are summed up to E_L. To include a future energy gain from possible PV modules, pre-evaluated solar roof data is included. The annual calculated solar gain is represented by E_G. To calculate an annual electrical **self-sufficiency rate** r_{ss} following ratio is defined:

$$r_{ss} = \frac{E_G}{E_L} \tag{1}$$

The third attribute for clustering is the **grid access**. It differs the buildings by their possible access to existing energy grids. In Germany a building's connection to the electricity grid, especially in urban and semi-urban areas, estimates close to 100%. Additional energy grid connection to a gas grid or to district heating is very likely. The allocation of buildings to supply networks mainly relies on the maps given and the proximity of identified network segments to the buildings.

Starting with multiple data sources, an algorithm is formed that interleaves the described data sources and combines them to selected attributes.

2.3. Data sources

In the following paragraph, the data sources and their pre-processing are presented.

Cadastral data. All building-related properties are extracted from a GIS open-access data set provided by the regional government [32] named ATKIS (Official Topographical Cartographic Information System). From the so called LoD2 building model [33] information about a building's base area perimeter, roof shape and its ridge height, as well as building's identification number, current use, and its address are extracted. A building that contains at least one dwelling may consist of several parts. These parts will most likely, but not necessarily, have the same building identification number. Only building parts that are defined to be residential buildings are extracted from the database [18]. The data sets are further reduced by combining building parts with the same identification number, same location, same address, or similar proximity. To reduce the amount of data these building parts were unified, by extending the properties of the biggest building part (by ground surface) to all building parts with same ID or location. Building parts with missing address data are added to the nearest address. Data sets with the same address within 100 m are also be joined to be represented as one. Buildings with n distinct house numbers in the

Table 2
Average electricity consumption in kWh in 2013 by household size [35].

Persons in Household	Observations	Median kWh/(flat x year)
1	649	1957
2	889	3528
3	294	4561
4+	273	4568

address are counted as a single building with n parts with the same properties.

A useful additional information that completes the typification of the IWU [31], but not included in the dataset, is the building type neighboring situation. It determines if a building is freestanding, without any contact to neighboring buildings or has one or two shared walls with the adjacent buildings. For this, the boundaries of all buildings are compared to the four nearest neighbors according to their location. If overlapping boundary points are found, they are considered accordingly.

A building's living area is needed for the assignment of flats, the estimation of inhabitants, and the building's age. For this the ground surface, the roof ridge height, and the roof type are used to estimate a usable living area per building. The results for the living area are adjusted according to the given data of the municipal statistics for the total living area per inhabitant.

Solar roof data. The solar roof data is a pre-evaluated data set made available to the public by the State Agency for Nature, Environment and Consumer Protection (LANUV) of North-Rhine-Westphalia (NRW) [34]. Roof surface data from LIDAR-scans were evaluated in terms of size, altitude, azimuth, and shadowing to calculate potential areas of PV modules and their solar electricity yield. Construction-related factors such as condition and static of the roof or building, as well as recessed roof windows and smaller roof disturbances like vents were not considered in this data basis. The annual solar power generation was pre-calculated based on technological development from 2015. Nowadays, these values give back the lower edge of the possible. Conveniently most identified potential solar roof surfaces were assignable to its building by the known building's identification number of the cadastral data. For some roof area this information was missing or could not be assigned. Since the majority of buildings are suitable for PV installation, the lesser error is to assign roofs without identified solar area to the nearest comparable solar roof (similar roof size within the next 10 buildings) on the same street and copy their data set corrected by the ratio of their ground areas.

Electricity demand data. The annual electricity consumption is taken from a study by RWI [35] as listed in Table 2, derived from observation of several households and their energy consumption.

Census data. As the energy use of electricity is referenced by a dwelling's inhabitants, governmental open data of its last population census (2011) [36] to estimate the number of persons living in a particular building is used. The census data is available in a gridded resolution of 100 m per 100 m. The statistical data is slightly distorted due to statistical error as well as privacy protection. Additionally to the population data, the sizes per dwelling, number of building types, heating units, etc. were counted. Used data and their categories are listed in Table 3. The following adaption is implemented to improve the census data:

- Grid tiles without dwelling but with n cadastre buildings existent are counted as n buildings found
- Grid tiles without population but with dwellings are counted with interpolated population data of the area
- Grid tiles without residential buildings are neglected

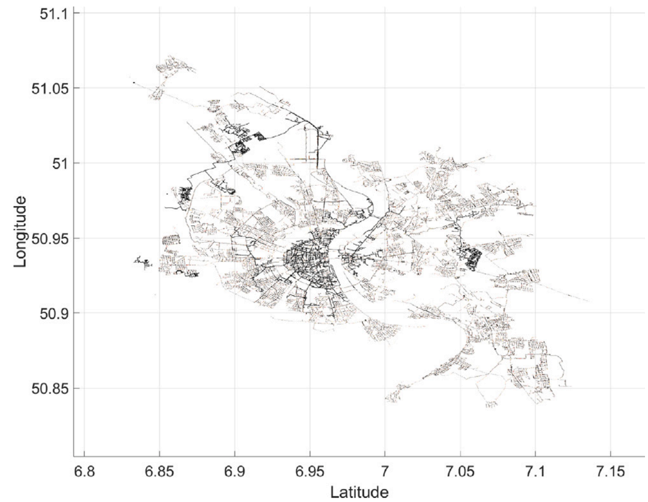

Fig. 3. Distribution map the city's gas grid (gray) and district heating (black) from data obtained by [38,39].

- Grid tiles with less population than buildings are counted with one person per flat
- Outliers with more than 700 m^2 living area per inhabitant or less than 10 m^2 living area per inhabitant are adjusted to fit the border

Nevertheless, this fine grid of data gives a good estimate of higher and lower populated areas and can easily be used to calculate inhabitants per m^2 of living area and therefore give a good estimation of number of inhabitants per flat or building. The local population density calculated are then be adjusted to fulfill the number of inhabitants for the whole region, as stated as official number in [30].

Map data. Two different types of network maps are used to determine whether a building is likely to be connected to the existing gas network or to a district heating networks. Maps from both networks were publicly available but with unknown date of origin. Similar grid connections might be estimable by analyzing heating needs or creating a synthetic grid similar to a city's street network [37]. The high-resolution district heating network is published on municipal provider's website [38]. The gas grid is obtained from a published pdf file with a maximum resolution of approx. 11622 × 12489 pixels [39]. Depending on the different map resolutions, networks are assigned in order. Buildings connected to district heating are not connected to the gas network, even if the gas network is in front of the building. Gas connections are assigned street by street with an almost exclusive quota. In Fig. 3 both networks are shown in an overlay. As central heating system for living quarters might stretch over several buildings an adaption with data from the census is made in grid tiles with majority allocation to district heating. Nevertheless, a higher non-assignment of attached living quarters is likely.

Municipal statistical data. The municipal statistical data is published by the city's own statistic department [30]. As this statistical data is more recently published, it is used to correct the approximation of the living area to a reasonable verified number. Also, the overall population is adapted to newer values, but the distribution stays as quoted by the census data.

2.4. Data processing

Fig. 4 shows a simplified schematic of the data processing during the classification procedure. It shows, how data, originating from several source databases, are combined, corrected and collected in interim attributes to result in three target attributes to characterize a specific

Table 3
Categories of the extracted census data set [36].

Living area (# bldgs of m^2 cat.)	Population (# inhabitants)	Building type (# buildings)	Construction date (year range)	Heating type (# units)
Below 30	Total	Detached SFH/DFH	Before 1919	DH
30–39	Sex (male/female)	Semi-detached SFH/DFH	1919–1949	Apartment heating
…	Age distribution	Terraced SFH/DFH	1950–1959	Block heating
170–179	(ten years age groups)	3–6 dwellings in AB	…	Central heating
180 and more	Age distribution	7–12 dwellings in AB (BAB)	1990–1999	Individual stoves
	(five classes of years)	13+ dwellings in AB (LC)	2000–2005	
		(other)	2006 and later	

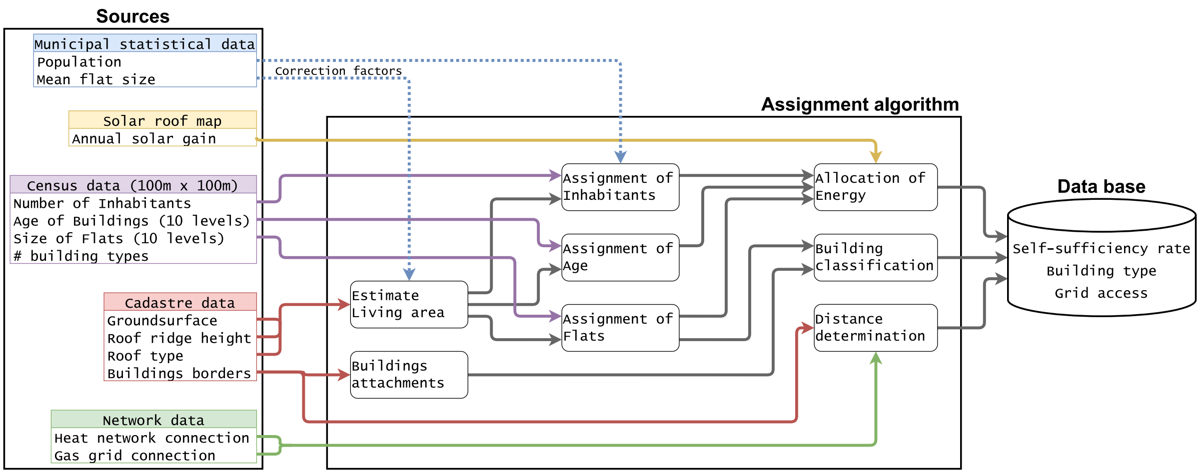

Fig. 4. Simplified schema of data sources and their use in the algorithm.

building. A connection of different data sets in between the databases is made on basis of same ID, in the case of cadastre data to solar roof map, or location of building for connecting cadastre data, census and network data.

Assisting interim attributes have to be calculated and assigned. As interim attributes serve:

(a) the building attachments — a building's shared walls to its neighbors
(b) the living area — floor space occupied by dwellings
(c) the number of flats in a building
(d) the number of inhabitants in a flat/building
(e) the age of the building — related to different energy standards

On basis of the interim attributes, the three target attributes (building type, self-sufficient rate, and building's grid access) are determined by three processes:

- the classification of a building as a defined type
- the allocation of annual PV production and energy demand to calculate the self-sufficiency rate
- the distance determination between a building to the next available energy grid (GG, DH) sets the grid access

Starting with an analysis of the given boundaries of all buildings from the LOD2 model, the four closest buildings (by location) are checked for matching points to determine a **building's attachment**, or in other words, if a building is free-standing or shares walls with one or more buildings.

More important is the **estimation** of a building's **living area**, as it influences all three assignments of flats, inhabitants, and a building's age which are all used to calculate the building's energy balance. The estimation of the building's living area is based on the given ground surface, the measured roof ridge height, and the roof shape. The different roof shape types are acknowledged by a rough factor for the highest floor space. The number of floors is estimated by the roof ridge height of the building part divided by the most common floor height around 2.8 m. For larger multi-story buildings, a deduction of 10% of the living area is made to account for common stairwells, lifts, walkways, and walls. This deduction plays a minor role, as the total living area is subsequently corrected by a factor to consider the official statistical data of the municipality from 2019.

The **assignment of inhabitants** is performed with data from the census. In each tile of the census, the number of inhabitants is divided by the sum of flat space (given in 10 flat size categories), to calculate a local population density. Boundary tiles without data are extrapolated from nearby tiles. A minimum occupancy of one person per flat is assumed. This population density is then used with the estimated living area to calculate the number of inhabitants per building.

The **assignment of flats** follows a similar approach. In each map tile of the census a count of flats per building type is given. As the building type is not yet known, the overall flat count per map tile affects its procedure. If no additional census data is available, the overall mean flat size of 76 m^2/flat is used to determine a buildings number of flats. If a flat count in more than 3 house types are given, the frequency distribution is used to assign single dwellings to the lower end of living area values per building and more flats to the possible AH with higher living area values. A third case is in between given cases, here the flat count is used to calculate a mean size of a flat and assign a certain number of flats per building accordingly.

The **assignment of age** is made by overlaying the frequency distribution of the buildings' volume and the frequency distribution of the buildings per age following the assumption, that similar buildings are constructed in a similar time frame. As the distribution is also based on the census data in 100 m × 100 m map tiles, the overall influence on the final energy balance is acceptable.

The **building classification** is based on a previous analysis of the building flat assignment and the subordinate building attachment. Based on these attributes, the predefined building type is assigned to the building dataset.

The **allocation of energy** quantities from solar roof generation and electricity load is achieved with the following procedure. For the solar roof gain, the pre-calculated annual gains are provided by the assigned dataset. The electricity consumption is taken from RWI [35]. It depends on the household size. A building's electricity consumption is determined by assigning the median value for electricity consumption per flat and household size to each dwelling and totaled accordingly per building. The self-sufficiency rate is then calculated according to Eq. (1). A future extension of the self-sufficiency rate using a cross analysis with heat loads per house type based on IWU [31] is conceivable.

The **distance determination** considers whether a building is connected to an existing district heating or to the existing gas grid. With the higher resolution of the district heating network the assignment is performed by comparing whether a coordinate of the network lines is actually inside or near the building's ground borders. Since there are building blocks with central heating for more than one building, and the attached buildings were not connected to the network, additional data from the census is used. Buildings in map tiles with a high to exclusive use of district heating, as indicated by the census data, were also assigned as users of the district heating network.

For all other buildings, the distance from the building location to the nearest gas grid point is counted, which is obtained by detecting gas pipes in the gas grid image. The resolution only allows to check if a street or a part of a street is equipped with the GG. Therefore, a building is counted as 'gas grid available' if the distance to the next gas grid point is less than the usual street width of about 10 m plus a distance for the location point to its ground boundary, estimated by half the square root of its ground surface.

3. Results

The following result graphs and values are based on the previously described data sources and the current development state of the algorithm. Nearly 300,000 data sets for buildings or building parts are found in the cadastral data that belong to the Cologne city area and are analyzed for the purpose of this work. About 172,000 building parts are identified for residential use. From the solar potential data base all roof entries were scanned and accumulated to about 163,000 solar roofs on buildings or building parts. A first matching, by ID, results in 132,000 building parts with data of solar potential. Further joining of these building parts by building ID, address and proximity, leaves about 134,000 building units with only 19,000 roofs without data. As described above, missing solar roof data is generated from nearby buildings for these buildings leaving finally only 1.3% of the buildings without solar roof data.

The official data from the city has 143,556 residential buildings listed for 2019. Nearly 147,000 data entries of buildings with residential purpose are counted by the algorithm using ID, location, and address as separation or unification units. This is a good indication of consistent building count. The assignment of flats in a building groups these into 5 categories. The survey identified 90,107 SDFHs, 26,184 ABs, 13,437 BABs, and 4,304 LQs in the considered area. Regarding the connection of buildings to each other, the algorithm identified 30,085 free-standing buildings, 50,119 buildings with one and 53,828 buildings with two or more shared wall sections with neighboring buildings.

A heat map is used to visualize the results from analyzing residential buildings for each of the three scenarios by distribution of building types across the entire city area. The map highlights different districts with similar building types. In each heat map the city center is marked with two concentric circles of 2.5 and 5 km radius. A corresponding statistical evaluation of the electrical self-sufficiency rate by building type is shown by a box plot. The horizontal red line in the box plots represents a self-sufficiency rate of one. Buildings above this line indicate a surplus of electrical energy within a year, while those below

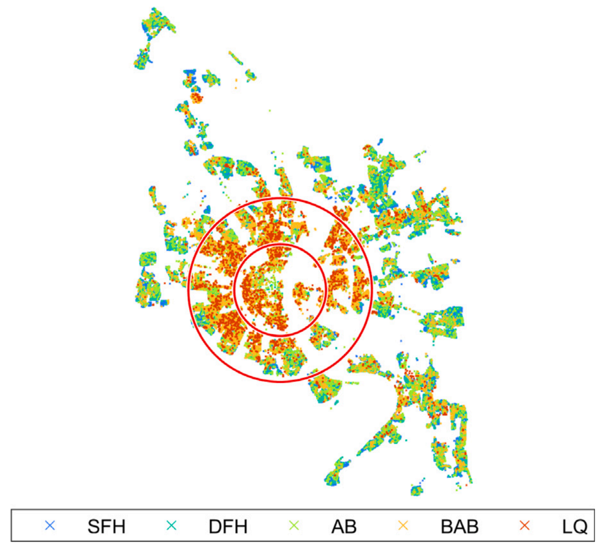

Fig. 5. Heat map of confident building types connected to GG and power grid.

the line require additional electrical energy to meet their needs. Several key elements can be observed in the box plot. First, the median value represents the central tendency of the data distribution. It provides an indication of the typical solar energy to energy need ratios for the different building types. Buildings identified as outliers, with more than three scaled median absolute deviations, are shown as individual data points outside the whiskers in the box plot. These datasets are discarded as they do not represent the common range of a building type specific self-sufficiency rate and are therefore not shown in the heat map. The inner quartile data points, shown in the box plot, are considered representative buildings for the scenario cases. These data points provide a more accurate representation of energy production and consumption for each building type. Overall it can be observed, that single-family homes (SFH) tend to have a higher solar energy input per living surface compared to multi-family homes (MFH) or living quarters (LQ) with more stories. This suggests that SFHs have a greater potential for self-consumption of own produced solar energy.

The heat map in Fig. 5 shows all buildings by type which are connected to the extended GG. It is noticeable that the inner city area has a higher density of apartment buildings (AB) to living quarters (LQs), while the outer city area has more buildings functioning as single/double-family homes (SDFH) to smaller apartment buildings (AB) with 3–13 dwellings. Based on the analysis of the inner quartile data points and the self-sufficiency rate, the conclusion is, that there is an overall higher self-sufficiency rate in the outer parts of the city. Given the higher proportion of SDFH in the outer parts of the city, it is likely that these building types contribute to the overall higher self-sufficiency rate observed in these areas. This suggests that the outer parts of the city have a greater potential for renewable energy generation and less dependence on external energy sources.

In Fig. 7 the heat map with buildings connected to the district heating grid is shown. As observed previously, Cologne has a larger central grid and several smaller district grids for district heating distribution. In the map, these buildings connected to these grids are depicted and the district-wise smaller grids are shown clearly separated from the central grid. Connected to the city center grid, the building types of AB, BAB and LQ are prevalent. Clearly identifiable are some districts of the outer city area, were only SFH to DFH buildings are connected to one of the smaller DH grids.

However, when examining the data set of connected residential buildings, it becomes apparent that the data base is reduced, as indicated by the point density of outliers in corresponding data set in

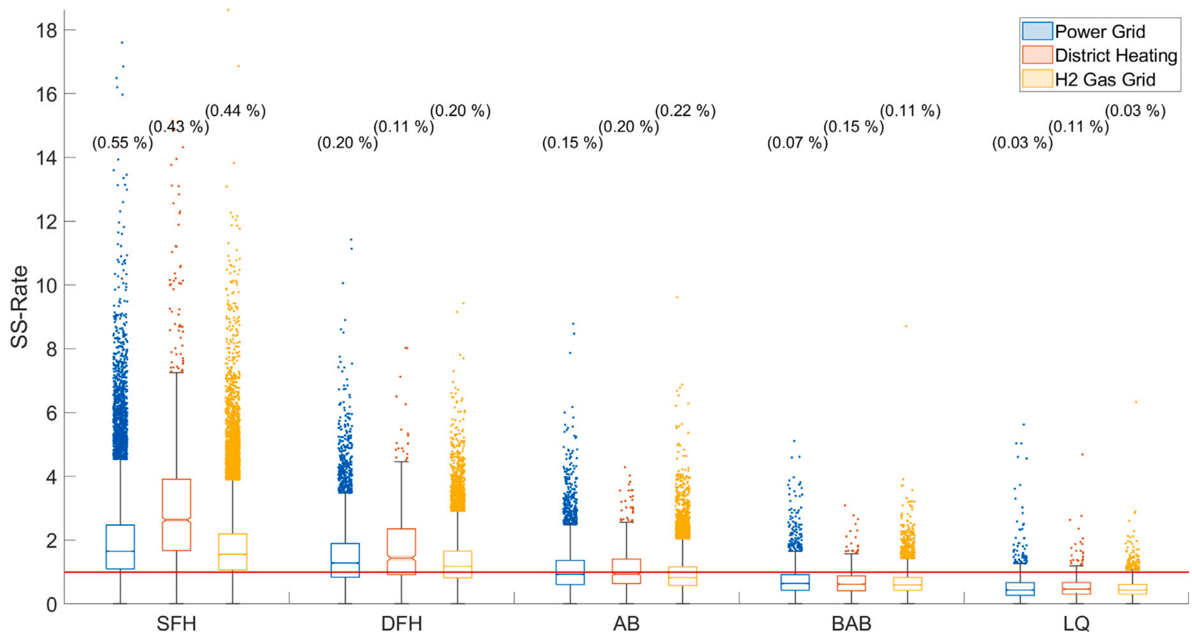

Fig. 6. Box plot of building types connected to different grids, horizontal red line indicates self-sufficiency rate equal to one.

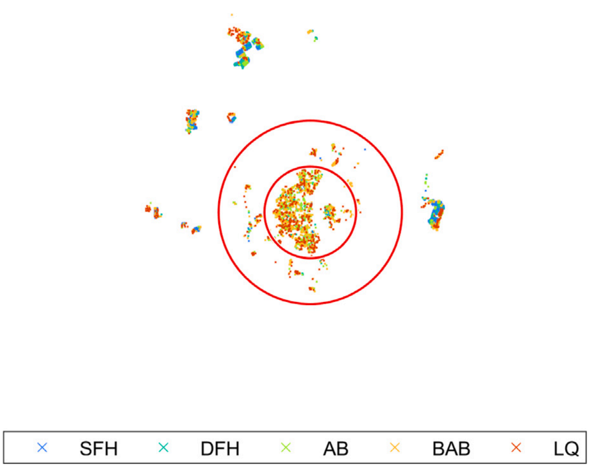

Fig. 7. Heat map of confident building types connected to DH and power grid.

Fig. 6. Next to the GG, the number of residential buildings connected to DH is small. Only about 5% of all identified residential buildings are connected to the DH grid. The self-sufficiency rate of SDFH in this case is even higher compared to the other two scenarios. Especially in the outer city area, as seen in the heat map, some districts are nearly solely occupied by single-family and double-family homes (SDFH). This suggests that these types of buildings have a greater potential for surplus energy generation or a reduced need for additional electrical energy. By identifying the districts' prevalent buildings style, the buildings attributes can be traced back to flat roof single-story houses. This building style was particularly prevalent in the 1970s and 1980s. Flat roofs provide ample space for the installation of solar panels, allowing for sufficient solar energy generation. In addition, the age of the buildings suggests that the occupancy is currently relatively low due to demographic changes and combined with the single-story nature of these houses, energy use is in the lower range, resulting in overall higher self-sufficiency rate.

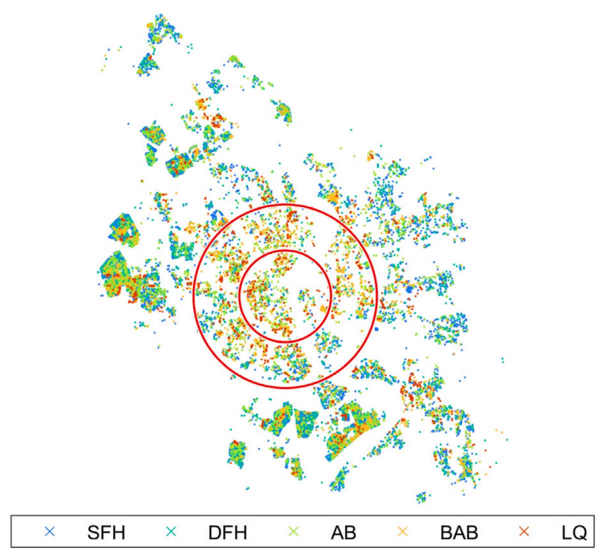

Fig. 8. Heat map of confident building types only connected to the power grid.

In the last set of results, the examination of the heat map (Fig. 8) shows all the buildings that are neither connected to the gas grid (GG) nor district heating (DH). The density of buildings in this heat map gives a clear insight into the concentration in the outer districts of the city with building types leaning in the SFH to AB range.

Several observations can be made when analyzing the map. First, in these outer districts there is a significantly higher number of single-family homes (SFH) compared to other building types. Accordingly there is a prevalence of SFH in areas where GG or DH connections are not present. Also districts with same building types are clearly seen and can be separated and identified for real world comparison. Additionally, when looking at the self-sufficiency rate of all building types (Fig. 6), their mean value is set slightly higher compared to the gas grid scenario. This can be attributed to a higher solar energy yield per living area than in the more central districts. The abundance of SFH in these areas allows for a greater potential for solar energy generation, resulting in a higher self-sufficiency rate.

4. Discussion

As shown in the previous chapter, public data can be used to classify buildings in urban areas according to building type, self-sufficiency rate, and grid access. Self-sufficiency is estimated on the basis of net energy demand considering photovoltaic rooftop potential as well as building-type dependent heat and electricity demand distinguishing different types of grid access. With a newly developed algorithm, a representative energy load of each building can be calculated. For this, each building is classified based on specific attributes and the energy demand is estimated.

A representative amount of all buildings in the whole city is evaluated. The buildings are paired with official statistical data to estimate the occupancy of each building. The number of flats and persons per building brings more detail to the analysis and improves the energy demand estimate compared to regular citywide averages. For the allocation of the buildings to the infrastructural energy grids some adjustments could be made to known building indicators, but the analysis certainly does not reflect complete and unambiguous allocations of buildings to specific networks. Additionally, various inconsistencies between the datasets, including different data set recording dates, ID mismatches, and missing data due to data protection, result in outliers. Some of these can be avoided by possible compensation, e.g. by filling in data from neighboring solar roofs. Nevertheless, the energy dispersion in the building type class is relatively high, but the inner quantiles are well represented and therefore the outliers are easy to identify.

Understanding the historical context and architectural features of districts provides valuable insights into the factors contributing to the observed self-sufficiency rate variations. This knowledge can inform future urban planning and energy management strategies, promoting sustainable and energy-efficient building designs that align with the specific characteristics of different regions and grid connections within the city.

This work focuses on the individual building level and its yearly energy demand by including sample energy assessments of end energy use, similar to evaluated data sets by [13,40]. Details about the buildings inhabitants are not known, therefore a creation of demand profiles based on the occupant behaviors, like conducted by [41], are not included.

The use of open and public datasets is very beneficial in terms of availability, statistical range, and protection of privacy, but it also has its challenges in terms of missing or conflicting data as well as unclear definitions. Due to the chosen area and its size, the availability of the data and the resolution are of crucial importance. The selected datasets that form the input have a good overall resolution, with the coarsest defining the horizon of observation, which in this case is the population census data, limiting the resolution to 100 m × 100 m tiles. The identification of single buildings and their energy demand might vary, due to unification of population density over a single tile. Identifying similar districts and summarizing the energy demands of these are a very useful tool for planning and development of energy grids, as well as in this case, looking for potential placement and sizes of technology implementations.

The used data sets are available for many German or European metropolitan areas. If cadastral data might not be available, building attributes can be extracted to a certain accuracy from maps, GIS, LIDAR or satellite data. Solar potential data might be derived from this geometrical data set as well, in combination with irradiation data. Statistical data can be included in coarser resolution if governmental census data is not given. In general, the method developed with the assumptions presented can also be applied for the classification of other urban and semi-urban areas including the assessment of their grid infrastructure.

5. Conclusion

The method used to classify buildings for bottom-up energy demand mapping was successfully applied to all three scenarios. The same approach can be performed to assess similar housing situations in other urban or suburban areas.

Applying the bottom-up method to a restricted area, evaluating the whole amount of individual buildings leads to a distribution w.r.t the targeted parameters. In each distribution of exclusive parameters, a statistical evaluation provides information such as median and range from building types and their energy demand. The individual median building or locally clustered similar buildings can serve as representative and will enhance energy demand and grid use simulations. The use for identifying similar districts and summarizing the energy demands of these are a very useful tool for planning and development of energy grids, as well as in this case, looking for potential placement and sizes of technology implementations.

Understanding the relationship between building types, gas grid, and district heating connectivity, and the self-sufficiency rate supports energy planning strategies and contribute to the development of more sustainable and energy-efficient urban areas. By promoting the expansion of district heating infrastructure and encouraging the adoption of energy-efficient building designs, cities like Cologne can work towards achieving their energy and sustainability goals. The future role of the gas grid has to be determined. A re-dedication of existing natural gas pipelines to build up a hydrogen grid is feasible and might play a role in future energy distribution.

The research presented in this paper forms a basis for future work. With identified districts, matching the scenarios, a multiphysical simulation model will be created in MEgy simulator [4]. Calculated energy demand and surpluses are to be used as key inputs to optimize storage sizes. Following the method suggested by [3], a metamodel that can be created from the dynamic simulation results will be used for the sizing optimization. In addition, planned hydrogen generator plants as well as (possibly retrofitted) combined heat and power plants shall be taken into account. Respective models and data from [42,43] shall be incorporated.

CRediT authorship contribution statement

Steffen Schedler: Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Stefanie Meilinger:** Writing – review & editing, Supervision, Methodology. **Tanja Clees:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used DeepL Translate/Write in order to make the text more readable. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Acknowledgments

This work was supported by the German Federal Ministry for Education and Research, Germany [FHprofUnt FlexHyX project, grant number 13FH172PX8] and by the German Federal Ministry for Economic Affairs and Climate Action, Germany [Project SimBenchSektor, grant number 03EI1058C].

References

[1] Bundesministerium für Wirtschaft und Klimaschutz. Energiedaten: Gesamtausgabe. 2022, URL https://www.bmwk.de/Redaktion/DE/Artikel/Energie/energiedaten-gesamtausgabe.html.
[2] Wirth H. Aktuelle Fakten zur Photovoltaik in Deutschland. 2023, URL http://www.pv-fakten.de.
[3] Bareev-Rudy M, Steinebach G, Clees T. Optimal sizing and control of a hydrogen-based hybrid energy storage system by means of metamodeling. In: Proc. 22th ECMI conf. on industrial and applied mathematics. 2023.
[4] Bareev-Rudy M, Meiswinkel S, Pfennig M, Schedler S, Schiffer B, Steinebach G, et al. Analysis of Power-to-Gas-to-X systems with metal hydride storage based on coupled electrochemical and thermodynamic simulation, Energy Convers Manage, Manuscript submitted for publication.
[5] Clees T, Baldin A, Klaassen B, Nikitina L, Nikitin I, Spelten P. Efficient method for simulation of long-distance gas transport networks with large amounts of hydrogen injection. Energy Convers Manage 2021;234:113984. http://dx.doi.org/10.1016/j.enconman.2021.113984.
[6] Paulick S, Schroth C, Guddusch S, Rühling K. Resulting effects on decentralized feed-in into district heating networks – A simulation study. Energy Procedia 2018;149:49–58. http://dx.doi.org/10.1016/j.egypro.2018.08.168.
[7] Swan LG, Ugursal VI. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renew Sustain Energy Rev 2009;13(8):1819–35. http://dx.doi.org/10.1016/j.rser.2008.09.033.
[8] Meinecke S, Sarajlić D, Drauz SR, Klettke A, Lauven L-P, Rehtanz C, et al. SimBench – A benchmark dataset of electric power systems to compare innovative solutions based on power flow analysis. Energies 2020;13(12):3290. http://dx.doi.org/10.3390/en13123290.
[9] Thomsen J, Fuchs N, Meyer R, Wanapinit N, Ulffers J, Bavia Bampi B, et al. Bottom-Up Studie zu Pfadoptionen einer effizienten und sozialverträglichen Dekarbonisierung des Wärmesektors. Studie im Auftrag des Nationalen Wasserstoffrats. 2022, URL https://www.wasserstoffrat.de/veroeffentlichungen/studien,
[10] Fiedler C, Greif S, Schmid T. Potenzialanalyse zur Nutzung von Erdwärmepumpen im Gebäudebestand - Oberflächennahe Geothermie im außerstädtischen Wohngebäudebestand. BWK – Das Energie-Fachmagazin 2018;(7/8). URL https://www.ffe.de/veroeffentlichungen/potenzialanalyse-zur-nutzung-von-erdwaermepumpen-im-gebaeudebestand-oberflaechennahe-geothermie-im-ausserstaedtischen-wohngebaeudebestand/.
[11] Meha D, Novosel T, Duić N. Bottom-up and top-down heat demand mapping methods for small municipalities, case Gllogoc. Energy 2020;199:117429. http://dx.doi.org/10.1016/j.energy.2020.117429.
[12] Ali U, Shamsi MH, Bohacek M, Purcell K, Hoare C, Mangina E, et al. A data-driven approach for multi-scale GIS-based building energy modeling for analysis, planning and support decision making. Appl Energy 2020;279:115834. http://dx.doi.org/10.1016/j.apenergy.2020.115834.
[13] Calderón C, James P, Urquizo J, McLoughlin A. A GIS domestic building framework to estimate energy end-use demand in UK sub-city areas. Energy Build 2015;96:236–50. http://dx.doi.org/10.1016/j.enbuild.2015.03.029.
[14] Luthander R, Widén J, Nilsson D, Palm J. Photovoltaic self-consumption in buildings: A review. Appl Energy 2015;142:80–94. http://dx.doi.org/10.1016/j.apenergy.2014.12.028.
[15] Solar irradiance data | Solargis. 2023, URL https://solargis.com/.
[16] Frank CW, Wahl S, Keller JD, Pospichal B, Hense A, Crewell S. Bias correction of a novel European reanalysis data set for solar energy applications. Sol Energy 2018;164:12–24. http://dx.doi.org/10.1016/j.solener.2018.02.012.
[17] EU Science Hub. Photovoltaic geographical information system (PVGIS). 2023, URL https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis_en.
[18] Land NRW. Objektartenkatalog: ALKIS-OK NRW. 2019, URL https://www.bezreg-koeln.nrw.de/brk_internet/geobasis/liegenschaftskataster/alkis/vorgaben/pflichtenheft_03/anlage_03_alkis_nrw_ok_max_v6_0_1.htm#_3B2A042900B5-_3B2A042900B8.
[19] Quarton CJ, Samsatli S. Should we inject hydrogen into gas grids? Practicalities and whole-system value chain optimisation. Appl Energy 2020;275:115172. http://dx.doi.org/10.1016/j.apenergy.2020.115172.
[20] Rusman N, Dahari M. A review on the current progress of metal hydrides material for solid-state hydrogen storage applications. Int J Hydrog Energy 2016;41(28):12108–26. http://dx.doi.org/10.1016/j.ijhydene.2016.05.244.
[21] Pastore LM, Lo Basso G, Ricciardi G, de Santoli L. Smart energy systems for renewable energy communities: A comparative analysis of power-to-X strategies for improving energy self-consumption. Energy 2023;280:128205. http://dx.doi.org/10.1016/j.energy.2023.128205.
[22] Yilanci A, Dincer I, Ozturk HK. A review on solar-hydrogen/fuel cell hybrid energy systems for stationary applications. Prog Energy Combust Sci 2009;35(3):231–44. http://dx.doi.org/10.1016/j.pecs.2008.07.004.
[23] Hecht R, Meinel G, Buchroithner M. Automatic identification of building types based on topographic databases – a comparison of different data sources. Int J Cartogr 2015;1(1):18–31. http://dx.doi.org/10.1080/23729333.2015.1055644.
[24] Filogamo L, Peri G, Rizzo G, Giaccone A. On the classification of large residential buildings stocks by sample typologies for energy planning purposes. Appl Energy 2014;135:825–35. http://dx.doi.org/10.1016/j.apenergy.2014.04.002.
[25] Hecht R. Bebauungsstrukturklassifizierung für Nordrhein-Westfalen. 2017, http://dx.doi.org/10.13140/RG.2.2.11158.78401.
[26] Ferrando M, Causone F, Hong T, Chen Y. Urban building energy modeling (UBEM) tools: A state-of-the-art review of bottom-up physics-based approaches. Sustain Cities Soc 2020;62:102408. http://dx.doi.org/10.1016/j.scs.2020.102408.
[27] Selzam P, Horst DH, Hoffstede U, Nagel M, Wenger S. GeoOPT-bio: Geografische Energiesystem-Analyse zur Optimierung des Einsatzes von Biomasse im Energiesystem. 2022, http://dx.doi.org/10.2314/KXP:1872311113.
[28] Eurostat. Statistical regions in the European Union and partner countries: NUTS and statistical regions 2021. Manuals and guidelines / Eurostat, 2022 ed.. Luxembourg: Publications Office of the European Union, Europäische Kommission; 2022, http://dx.doi.org/10.2785/321792.
[29] Cadenbach AM, Abdurahmanovic N, Tarek A, Jahn A, Kaiser A. EQ-City – Pre-planning approach for an efficient and environmentally friendly heat supply of quarters and cities. In: Proc. 18th international symposium on district heating and cooling, 2023.
[30] Amt für Stadtentwicklung und Statistik. Kölner Statistische Nachrichten. (8). 2021.
[31] Institut Wohnen und Umwelt. Tabula: Further development of the German residential building typology. 2012, URL https://www.building-typology.eu.
[32] Bezirksregierung Köln. ALKIS - 3D-Gebäudemodell LoD2 (CityGML): Datenlizenz Deutschland - Zero - Version 2.0. 2022, URL https://www.bezreg-koeln.nrw.de/geobasis-nrw/produkte-und-dienste/liegenschaftskataster/.
[33] Bezirksregierung Köln. 3D-Gebäudemodelle: Produktbeschreibung. 2022, URL https://www.bezreg-koeln.nrw.de/geobasis-nrw/produkte-und-dienste/3d-gebaeudemodelle.
[34] Landesamt für Natur, Umwelt und Verbraucherschutz Nordrhein-Westfalen. Energieatlas NRW: Verwendung von Daten von Landesamt für Natur, Umwelt und Verbraucherschutz NRW, URL https://open.nrw/dataset/507aef70-938a-44df-83e6-45cc913d05331.
[35] Frondel M, Ritter N, Sommer S. Stromverbrauch privater Haushalte in Deutschland: Eine ökonometrische Analyse: Diskussionspapier. Z Energiewirtschaft 2015;39(3):221–32. http://dx.doi.org/10.1007/s12398-015-0157-0.
[36] Statistische Ämter des Bundes und der Länder. Zensus 2011 - Methoden und Verfahren. 2015.
[37] Esch T, Taubenböck H, Geiß C, Schillings C, Nast M, Metz A, et al. Potenzialanalyse zum Aufbau von Wärmenetzen unter Auswertung siedlungsstruktureller Merkmale. 2011, URL https://elib.dlr.de/76816/1/Waermenetzpotenzial_DLR_Endbericht_final.pdf.
[38] Rheinenergie. Map District Heating, URL https://www.rheinenergie.com/de/privatkunden/waerme__wasser/waerme/fernwaerme_beziehen/fernwaerme_beziehen.html.
[39] Stadt Köln. Datenbereitstellung zur Vergabe von Gaskonzessionen - Köln - Netzkarte, URL https://www.stadt-koeln.de/mediaasset/content/pdf15/gasverteilnetz_hauptdatenblatt.pdf.
[40] Bundesministerium für Wirtschaft und Arbeit. Energieverbrauch der privaten Haushalte und des Sektors Gewerbe, Handel, Dienstleisungen (GHD) URL https://www.bmwk.de/Redaktion/DE/Downloads/Studien/erhebung-des-energieverbrauchs-der-privaten-haushalte-2002-und-des-ghd-sektors-2001-kurzfassung.html.
[41] Pflugradt N, Stenzel P, Kotzur L, Stolten D. Loadprofilegenerator: An agent-based behavior simulation for generating residential load profiles. J Open Source Software 2022;7(71):3574. http://dx.doi.org/10.21105/joss.03574.
[42] Pfennig M, Schiffer B, Clees T. Thermodynamical and electrochemical model of a pem electrolyzer plant in the megawatt range with a literature analysis of the fitting parameters. Int J Hydrogen Energy 2024. http://dx.doi.org/10.1016/j.ijhydene.2024.04.335.
[43] Schiffer B, Pfennig M, Clees T. Comparison of hydrogen-based power plant technologies with a focus on district heating in Germany. In: Procs. 18th conf. sustainable development of energy, water and environment systems. 2023.